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Leveraging Deep Pre-trained Networks for Advanced Skin Lesion Classification for Human Monkeypox Detection

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Abstract: In response to recent human monkeypox outbreaks, the imperative of swiftly identifying and isolating infected individuals to curb transmission underscores the significance of innovative solutions. This study introduces an Android mobile application harnessing deep learning capabilities to address this urgent need. Developed using Java within Android Studio and Android SDK 12, the application leverages the device's camera via the Camera 2 API for real-time image capture. The captured video images are processed by a deep convolutional neural network (CNN) embedded within the device. Training the CNN involved utilizing a dataset containing skin lesion images from monkeypox-infected individuals and other skin conditions, employing a deep transfer learning methodology. The training and testing phases were executed using Matlab, with the selected network further trained using TensorFlow and adapted into a TensorFlow Lite model for mobile deployment. Successful testing on various devices yielded average inference times of 197 ms, 91 ms and 138 ms, affirming the application's efficiency. Facilitating swift preliminary diagnosis, the application empowers individuals with skin lesions to seek prompt medical attention, potentially curtailing disease transmission. Notably, the system exhibits a commendable 91.11% accuracy in classifying images, indicating its reliability. Moreover, its adaptable architecture suggests broader utility for training in diagnosing diverse skin diseases, reflecting a promising avenue for future healthcare innovations.

Introduction

As the globe continues to struggle with the repercussions of the COVID-19 epidemic, the new outbreak of monkeypox has caused serious worries within the international community. Although the World Health Organization (WHO) has not yet declared monkeypox a worldwide emergency, medical groups such as the World Health Network (WHN) are promoting prompt and well-coordinated measures to combat the illness (WHO, 2022; Hirani et al., 2023). Clinical signs and symptoms of chickenpox, measles and smallpox are similar to those of monkeypox, a zoonotic illness associated with the Orthopoxvirus genus (Bunge et al., 2022; Zardi and Chello, 2022; Thakur et al., 2023). Medical practitioners may find it difficult to diagnose skin infections early on due to their relative rarity and resemblance to other disorders (Kaur, 2023; Kumar et al., 2023; Panda et al., 2023). Furthermore, it might not always be possible to obtain confirmatory Polymerase Chain Reaction (PCR) testing.

Given a predicted case fatality ratio of 3-6% for the latest pandemic (Bunge et al., 2022), early detection, contact tracing, and isolation are crucial measures to prevent the spread of the virus within communities. The potential for AI-based technologies to significantly mitigate the global spread of monkeypox is noteworthy (Ferreira, 2020; Deng et al., 2024; Kundu et al., 2024). Machine learning (ML), a subset of artificial intelligence (AI), has demonstrated utility across various domains, including industrial sectors, medical imaging and disease

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diagnosis. Deep learning (DL), a powerful ML technique, offers rapid and accurate imaging solutions that serve as valuable decision-making aids for healthcare professionals (Bragazzi et al., 2022; Taylor, 2022).

DL models, characterized by their ability to analyze images at multiple levels and extract crucial information automatically, have shown promise in identifying various pox types (Liu et al., 2017; Yan et al., 2018; Ozbay and Alatas, 2020; Lu et al., 2021; Chen et al., 2024). However, the efficacy of DL-based systems is contingent upon access to extensive datasets and time-consuming training with specialized computing resources (Ali et al., 2022). Data augmentation, a common technique for expanding datasets, involves making minor adjustments to existing data to generate additional samples (Zumla et al., 2022).

Monkeypox manifests symptoms lasting 2 to 4 weeks, with severe cases posing considerable risks. Its incubation period typically spans 6 to 13 days, with varying durations observed. Clinical observations reveal two distinct phases: an initial invasion period marked by fever, back pain, lymph node swelling, headache, muscle aches, and fatigue, followed by the emergence of skin lesions within 1-3 days. Notably, facial lesions are prevalent in 95% of cases, while involvement of the palms, soles, oral mucosa, genitalia, and conjunctivae highlights the disease's systemic impact (Heymann et al., 1998; Ding and Tao, 2015; Liu et al., 2017; Zardi and Chello, 2022; Heskin et al., 2022; Altun et al., 2023).

Transmission primarily occurs through close contact or exposure to contaminated materials, necessitating stringent isolation protocols until lesions have healed. However, challenges persist in detecting cases promptly, compounded by limited access to Polymerase Chain Reaction (PCR) and biochemical testing resources (Yan et al., 2018; Ozbay and Alatas, 2020; Zardi and Chello, 2022; Laurenson-Schafer et al., 2023; Deng et al., 2024). To address these gaps, the study proposes an Android mobile application leveraging artificial intelligence and deep learning techniques for monkeypox detection. By analyzing skin lesions captured via smartphone cameras, the application empowers individuals to conduct preliminary diagnoses, facilitating timely medical intervention and containment efforts (Oztel et al., 2018; Deng et al., 2024; Kundu et al., 2024; Yue et al., 2024).

The innovation lies in the development of a cost-effective, non-invasive diagnostic tool, utilizing a modified MobilNetV2 model to detect monkeypox in humans—an unprecedented feat in mobile health applications (Sahin and Oztel, 2021). By bridging the gap between technology and public health, the study heralds a new era in disease surveillance and management, exemplifying the transformative potential of mobile devices in safeguarding global health (Gonzlez et al., 2022).

Background

Monkeypox, a zoonotic disease caused by the monkeypox virus, poses significant public health challenges globally, particularly in West and Central Africa. The United States experienced its first epidemic of monkeypox outside Africa, attributed to contact with sick prairie dogs in captivity, resulting in over 70 confirmed cases (Joshi et al., 2022). This incident underscored the potential for monkeypox to spread beyond endemic regions and highlighted the need for enhanced research efforts to understand its epidemiology, vectors, and transmission dynamics.

First identified in humans in 1970, monkeypox has garnered increased attention from researchers due to its rapid spread and clinical similarities to smallpox (Hung et al., 2021; Buono et al., 2022; Zardi and Chello, 2022; Heskin et al., 2022; Altun et al., 2023; Thakur et al., 2023; Deng et al., 2024). As the most dangerous orthopoxvirus infection since the eradication of smallpox in 1980, monkeypox exhibits extreme contagiousness, often manifesting as small clusters of cases that can escalate rapidly if not contained promptly (Amazon: Kindle for Android, 2022; Coca et al., 2021). The importation of sick animals or tourists has led to the emergence of monkeypox in new regions, necessitating global surveillance and response strategies (Coca et al., 2021; Dammak et al., 2022).

While research on human monkeypox dates back several decades, recent advances in computer vision and deep learning have revolutionized early disease identification and diagnosis. Many Authors (Heymann et al., 1998; Wilson et al., 2014; Alhasson et al., 2023) have utilized web mining algorithms to collect images for the categorization of monkeypox, chickenpox, measles, and normal skin conditions. Transfer learning methods, particularly using the VGG-16 model, have shown promise in accurately diagnosing monkeypox cases (Ladnyj et al., 1972; Breman et al., 1980; Alhasson et al., 2023). However, challenges remain, including the need to optimize model selection and interpretation for mass screening purposes (Cho et al., 2021).

In addition to monkeypox, deep learning models have been leveraged to identify various other illnesses, including chickenpox, herpes and skin disorders such as psoriasis and melanoma (Watts et al., 2020; Mamoun et al., 2021). Mamoun et al. (2021) explored the use of

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convolutional neural networks (CNNs) to categorize skin lesions with an accuracy rate of 78% using the VGG-16 pre-trained model. Other studies, such as the one by Berger-Groch et al. (2021), have demonstrated the efficacy of transfer learning techniques in recognizing diseases like measles and Ebola virus illness.

Despite these advancements, challenges remain in optimizing deep learning models for disease detection. Ahsan et al. (2022) highlight the need to address limitations in model functionality and interpretability, particularly for binary classification tasks. Meanwhile, efforts to enhance disease recognition using low-complexity CNNs and smartphone-based approaches like MobileNet show promise in improving diagnostic accuracy and accessibility [30]. Smartphones are playing a more and bigger part in the administration and provision of healthcare. Without requiring extra gadgets, people may keep in touch with their healthcare professionals and quickly obtain information about their health status thanks to mobile healthcare applications. With their well-known mobile devices, patients may easily access a range of healthcare services (Watts et al., 2020). The goal of a wide variety of mobile applications is to improve the provision of healthcare (Mamoun et al., 2021; Berger-Groch et al., 2021). As an illustration, certain apps concentrate on diagnosing skin lesions. Using deep learning techniques, researchers developed a mobile system in recent studies (Francese et al., 2021; Krohling et al., 2021) for the diagnosis of skin cancer lesions. A smartphone application that can recognize and detect moles in skin photos and classify them into benign lesions, nevuses and melanoma based on their severity was shown in a different research (Doukas et al., 2012). Moreover, researchers used computer vision and image processing techniques to create a smartphone application for the segmentation and categorization of psoriasis in a different study (Vasefi et al., 2017; Shuvo et al., 2021).

In conclusion, recent research efforts have significantly advanced our understanding of monkeypox and other infectious diseases, leveraging deep learning and computer vision technologies. However, continued collaboration and innovation are essential to overcome existing challenges and develop effective strategies for disease surveillance, diagnosis and containment.

Methodology

The system's operational framework, as depicted in Fig. 1, elucidates the steps involved in identifying human monkeypox lesions. Initially, the lesion images undergo meticulous preprocessing, which includes standardizing pixel values from the original range [0, 255] to a normalized scale of [-1, 1]. Following this preprocessing stage, the system undergoes a comprehensive training regimen utilizing transfer learning methodologies, leveraging pre-trained networks. During this phase, a range of pre-trained network designs is notably used, and their individual performances are carefully assessed and compared. This complex process of training and assessment is carried out on the Matlab 2022a environment. The network with the best performance metrics is then painstakingly re-built with TensorFlow, a powerful deep learning framework. The TensorFlow model is further streamlined and transformed into a TensorFlow Lite model to provide wider accessibility and usability, allowing for smooth integration with mobile and edge computing devices (Abadi et al., 2015; Tensor Flow Lite, 2022).

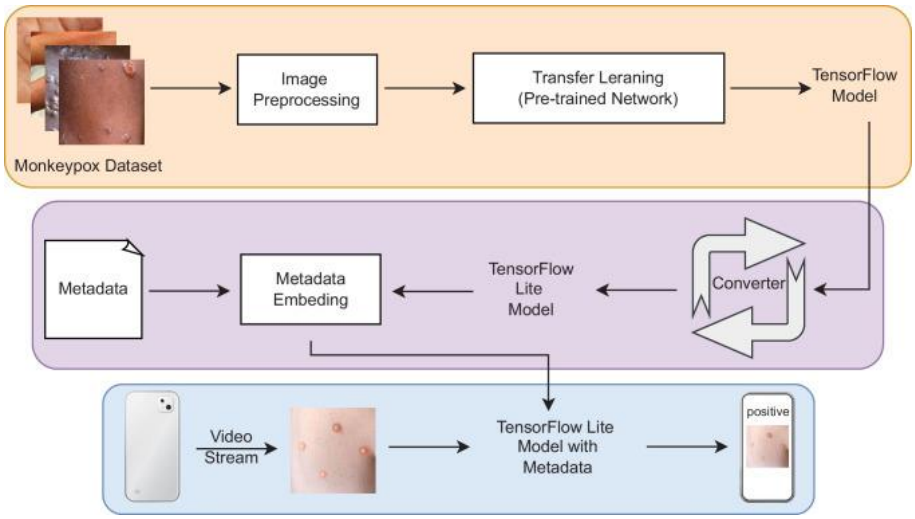

Figure 1. A perspective of the proposed method.

A crucial component of this project is the creation of an Android application designed to implement and run the TensorFlow Lite model for lesion

identification in monkeypox cases. The mobile application uses the smartphone camera feature to dynamically record and process live video feeds when they are activated. These streams are broken down methodically, with each picture frame going through strict categorization methods that are built into the program. This advanced analysis's result provides useful information on whether the lesion under investigation shows signs of monkeypox, positive or negative. In the event of suspected instances of monkeypox, our mobile application serves as an essential front-line tool, providing both individuals and healthcare professionals with prompt and accurate diagnostic capabilities. our allows for quicker intervention and containment measures (Mayya et al., 2016; Xie and Hu, 2017).

Deep learning techniques provide the capacity to automatically identify complex characteristics that are important for tasks involving the detection of patterns in images (Wang et al., 2021). Convolutional Neural Networks (CNNs) are a strong paradigm among these approaches that find use in several computer vision areas, including action identification, facial expression recognition, text recognition, face recognition, and gender and age categorization (Aydogdu et al., 2017; Duan et al., 2018). Interestingly, CNNs have shown very effective in biological settings, such as computer vision and pattern recognition tasks.

Typically, convolutional, pooling, and fully connected layers make up CNN designs. As seen in Eq. (1), the convolutional layer convolves filters with input data to produce a two-dimensional output (Gkioxari et al., 2015).

$$\begin{aligned} S(i,j) &= (I * K)(i,j) \\ &= \sum_m \sum_n I(i+m, j+n) K(m,n) \end{aligned}$$

The equation shows a convolution process, with "I" standing for an image in two dimensions, "K" for a two-dimensional kernel, and "S" for the two-dimensional output that the convolution process produced. 'I,J' is the matrix's index, and (m, n) is a representation of the filter's dimensions. Non-linear activation functions, such as ReLU, are frequently used after convolution to down sample input dimensions, while pooling layers are used in between (Al-Milaji et al., 2019; Bao et al., 2021). Dropout layers are used to reduce the likelihood of overfitting, and completely linked layers come before the classification layer by connecting to every node in the layer before it (Hamad et al., 2018; Shuvo et al., 2021).

After the CNN model is created, feed-forward training is applied to the network to establish parameters like filter numbers, stride values, and dimensions (Goodfellow et al., 2016). The cross-entropy loss function (Eq. 2) (MATLAB: crossentropy, 2022) is frequently used in training to assess how much the goal outcomes deviate from the network's predictions.

$$loss = -\frac{1}{N} \sum_{n=1}^{N} \sum_{i=1}^{K} T_{ni} ln Y_{ni}$$

In the equation, N and K are the number of observations and classes, respectively. Y is the input, and T is the target.

Within deep learning, transfer learning is a key tactic that allows pre-trained networks to be used for a variety of tasks by modifying learnt characteristics. This study uses several pre-trained networks and modifies their final layers for the classification challenge related to human monkeypox (Tensor Flow Guide, 2022). To prime the networks for the current classification job, additional layers specifically designed for binary classification are swapped for fully connected layers with learnable weights (Google: Android OS, 2022).

The selection of pre-trained networks is influenced by deployment strategies for mobile applications and computing efficiency (Google: Mobile App Developer Tools, 2022). On mobile systems, models with small sizes and parameter footprints are given preference in order to guarantee quick execution.

Table 1. Details of the pre-trained networks used as feature extractors.

Network Name	Depth	Size (MB)	Parameters	Input Size
ResNet18	18	44	11.7	224x224
GoogleNet	22	27	7.0	224x224
EfficientNetb0	82	20	5.3	224x224
ShuffleNet	50	5.4	1.4	224x224
MobileNetv2	53	13	3.5	224x224

The pre-trained networks used in the study are included in Table 1 below, along with their corresponding properties.

The primary goal of this study is to create a smartphone app that can classify cases of human monkeypox. As a result, we give preference to models

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with fewer dimensions and characteristics in order to guarantee effective performance on mobile devices (Platforms M.: React Native, 2022).

The process of creating a mobile application to identify lesions caused by human monkeypox starts with a well-defined problem statement that emphasizes the necessity of an intuitive user interface that can utilize a mobile device's camera to detect lesions. On the basis of the issue description, this study outlines three main requirements:

#Permit mobile device users to identify monkeypox lesions.

#Collect and supply the user and the prediction subsystem with the video stream captured by the device's camera.

#Calculate the lesion and show the outcome on the device's screen.

The writers decided to create the application for the Android platform due to the increasing popularity of devices that run the Android operating system. Many gadgets, such as tablets, smartphones, smartwatches, and smart TVs, are powered by the Android operating system. As a result, using the resources available in the Android ecosystem is considered the best method for developing applications. The Android 12 SDK (API level 31) is used for development, and the writers use Android Studio as their integrated development environment (IDE) (Google: Flutter, 2022).

Using the proper camera APIs that the Android platform offers is required in order to access the smartphone's camera and take video frames. Because the Camera2 API works with Android devices running 5.0 Lollipop and above, the writers choose to use it.

A machine learning (ML) library that works with edge and mobile devices is necessary to meet the third criteria. Among the solid options is TensorFlow Lite, which was created especially for using ML models on mobile and edge devices with limited resources (JetBrains: Kotlin Multiplatform Mobile, 2022). TensorFlow Lite, which supports a number of programming languages, including Objective-C, C++, Java, Python, and Swift, makes it easier to incorporate machine learning (ML) features into Android apps. Using the Java programming language's capabilities, the authors create the mobile application using the TensorFlow Lite package.

The design decisions pertaining to the development process are summarized in Table 2.

It is necessary to transform current models into a format that is compatible with TensorFlow Lite in order to deploy machine learning (ML) models on Android devices using TensorFlow Lite. This format's optimization for quick execution, portability, and compactness defines it. The deep learning network in this study was first designed and developed using Matlab. TensorFlow was then used to replicate the network (Song et al., 2021; BN et al., 2022; Cai et al., 2022), after which a TensorFlow model was created. After that, the TensorFlow model was transformed into the TensorFlow Lite model format, which was included in the Android application with ease.

When the mobile application receives data to be predicted, it converts it into a tensor format that

Table 2. Design decisions for the mobile application.

Feature Type	Feature Name
Mobile Device	Smartphone
Operating System	Android OS
IDE	Android Studio Chipmunk 2021.2.1
SDK	Android 12 SDK (API level 31)
Minimum SDK	Android 5.0 SDK (API level 21)
Programming Language	Java
Camera API	Camera 2 API
ML Library	TensorFlow Lite

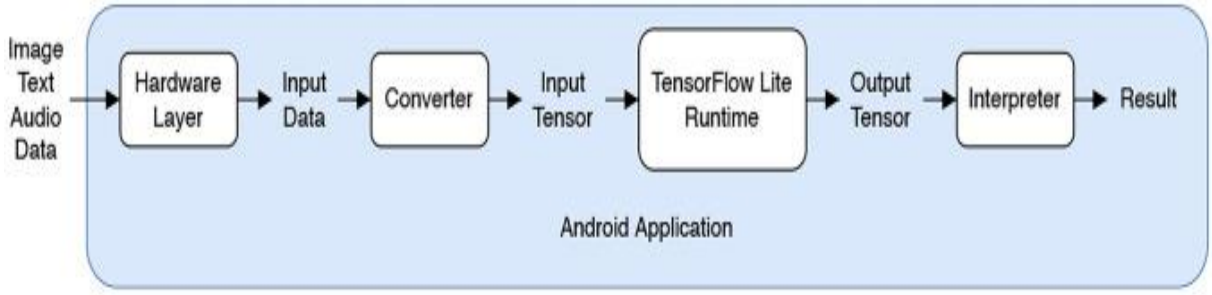

Figure 2. The flow of ML tasks on Android application.

TensorFlow Lite can use. TensorFlow Lite works with a tensor as its input data structure, which is similar to a multidimensional NumPy array. The tensor is then sent to the TensorFlow Lite runtime, which uses the tensor(s) that are supplied to coordinate the ML model's execution and produce the output tensor(s), which is how predictions are made. The interpretation of these tensors into prediction outcomes is the culmination of this stage, which is referred to as inference in the TensorFlow Lite environment (Mozilla: Progressive web apps (PWAs) MDN, 2022).

The TensorFlow Lite Task API and the TensorFlow Lite Interpreter API are two different APIs that TensorFlow Lite provides for machine learning tasks in Android applications. Although the goal of both APIs is to execute machine learning models, they are not the same in terms of functionality or level of abstraction. The TensorFlow Lite Interpreter API's functionality is encapsulated in the TensorFlow Lite Task API, which is used at a higher level in this study. One significant difference between both APIs is the metadata requirement: the TensorFlow Lite Task API requires model metadata to be included inside the TensorFlow Lite model, as seen in Figure 1.

Result

Use of the Monkeypox Skin Lesion Dataset (MSLD) (Ali et al., 2022) made the work of classifying human monkeypox easier. This dataset, obtained from the Kaggle website (NumPy: NumPy Homepage, 2022; Kaggle: Monkeypox Skin Lesion Dataset, 2022), consists of binary classification data for differentiating between lesions that are considered to be monkeypox and lesions that are not, such as measles or chickenpox, which are similar to lesions that are considered to be monkeypox. 102 images are from the monkeypox class and 126 images are from the non-monkeypox class. A variety of data augmentation techniques were used to enhance the original images, yielding an augmented image count of 1428 for monkeypox and 1764 for non-monkeypox. These techniques included hue, saturation, contrast adjustments, rotation, translation, reflection, shear, brightness jitter, noise addition, and scaling. These photos were enhanced and saved in the appropriate folder.

Moreover, the initial pictures were deliberately divided into test, validation, and training sets, preserving patient autonomy throughout. The roughly 70:10:20 ratio was maintained for the allocation among the sets. Notably, only the training and validation sets were subjected to data augmentation. The Fold1 folder, which functioned as the main resource for the training, validation, and testing stages of the suggested research, contained the datasets created in this fashion.

For the purpose of classifying human monkeypox, a number of pre-trained networks were modified and subjected to transfer learning for a maximum of 60 epochs. Prior to being customized for the proposed binary classification issue, which centered on monkeypox detection, these networks were trained to identify 1000 item types from the ImageNet database (Deng et al., 2009). In order to train the networks to distinguish between photos that had monkeypox and those that did not, the final layers were modified to fit the requirements of the job. Table 3 presents comparative data for the networks that show differences in accuracy between epoch numbers. Interestingly, after 60 epochs, MobileNetv2 and EfficientNetb0 showed the best results.

As shown in Table 4, a number of criterion indices were evaluated in order to gauge the efficacy of the

Table 3. Pre-trained network performances for the human monkeypox classification task.

Network Name	Epochs			
	15	30	45	60
ResNet18	**86.87**	66.67	75.56	73.33
GoogleNet	55.56	**82.22**	80.00	77.78
EfficientNetb0	82.22	88.89	88.89	**91.11**
ShuffleNet	77.78	77.78	**80.00**	**80.00**

The database was built with the intention of enabling computer-assisted identification of monkeypox from pictures of skin lesions. Web-scraping techniques were used to carefully compile MSLD from a variety of sources, including news portals, publicly accessible case reports, and pertinent websites. Original photos, enhanced images, and Fold1 are the three separate folders into which the dataset is arranged. The 228 photographs in the original images folder are divided into two classes: EfficientNetb0 and MobileNetv2 networks, which performed better in the human monkeypox classification test.

Figure 3 shows the confusion matrices for the MobileNetv2 and EfficientNetb0 networks, which have the highest accuracies. Furthermore, Figure 4 presents the system's visual results: (a) shows the outputs from EfficientNetb0, and (b) from MobileNetv2. The test set's example photos, which feature a range of

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backdrops and lesions from various body sections, validate the system's resilience.

The program uses the camera on the Android device as input, making use of the Android platform's Camera2 API. First, the camera's video stream is recorded and sent to the application interface. The next step is converting the video stream's frames from YUV to RGB format. The program interface further shows a preview of these frames.

Table 4. Objective evaluations of EfficientNetb0 and MobileNetv2.

Measure	Formula	EfficientNetb0	MobileNetv2
Jaccard	*TP / (TP+FP+FN)*	82.61	81.82
Precision	*TP/(TP+FP)*	86.36	90.00
Sensitivity	*TP/(TP+FN)*	95.00	90.00
F1 Score	*2*TP/(2*TP+FP+FN)*	90.48	90.00
Accuracy	*(TP+TN)/(TP+TN+FP+FN)*	91.11	91.11

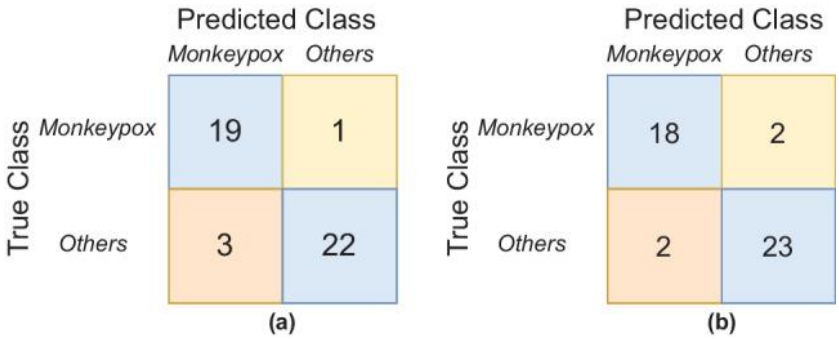

Figure 3. Confusion matrices of the networks which produced the best accuracy: (a) EfficientNetb0, (b) MobileNetv2.

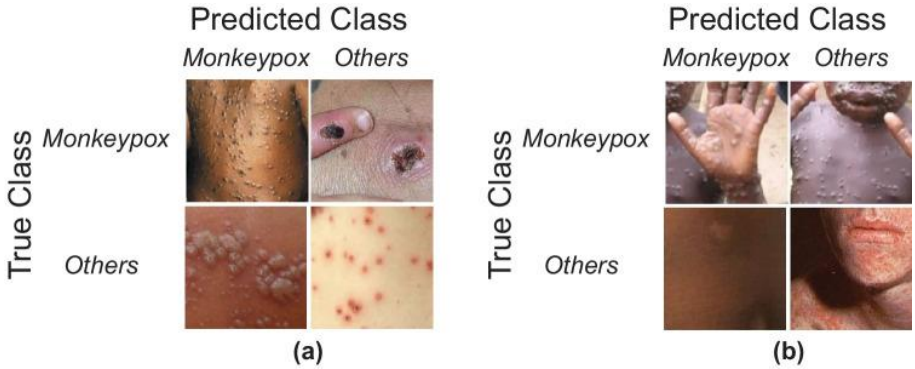

Figure 4. Some visual results of the networks: (a) EfficientNetb0, (b) MobileNetv2.

When compared to previous research, as shown in Table 5, the suggested system which specifically makes use of MobileNetv2-performs better than other approaches that use the same MSLD database in terms of precision, sensitivity, accuracy, and F1 score.

During the study's experimental phase, an Android mobile application that detects monkeypox was developed and tested. Instead of beginning from zero, the authors chose to base their work on the TensorFlow Lite GitHub repository's Image Classifier sample application (TensorFlow: TensorFlow Examples Repository, 2022). Under the open-source Apache License Version 2, this repository provides a range of sample applications for machine learning tasks, such as text classification, posture estimation, picture segmentation and image classification (The Apache Software Foundation: Apache License Version 2.0., 2022). We obtained and modified the Image Classification sample program to meet our needs for detecting monkeypox.

Subsequently, the TensorFlow Lite library's processed RGB pictures are passed into the Image Classifier object. Using the TensorFlow Lite model, the Image Classifier object conducts inference (prediction) and produces a list of recognitions for every picture frame. The program distinguishes between positive and negative classes, and these recognitions contain the classes and their accompanying probabilities.

Lastly, the program shows the inference time in milliseconds and the class name with the highest probability in the upper left corner of the device screen. Figure 5 provides sample screenshots of the built Android application showing true positives, true negatives, and false positives. Although there may

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occasionally be incorrect replies, the system generally produces excellent results. A dataset with more photos could be used to improve system performance.

The application was compiled with a minimum Android SDK version of 21 and successfully deployed and tested on three different Android devices. Throughout the runtime, inference times for each device were observed, and the average inference time for each device was calculated. Table 6 outlines the devices used for testing, highlighting differences in inference times, potentially attributable to varying characteristics of the mobile processor platforms such as GPU and image signal processor configurations.

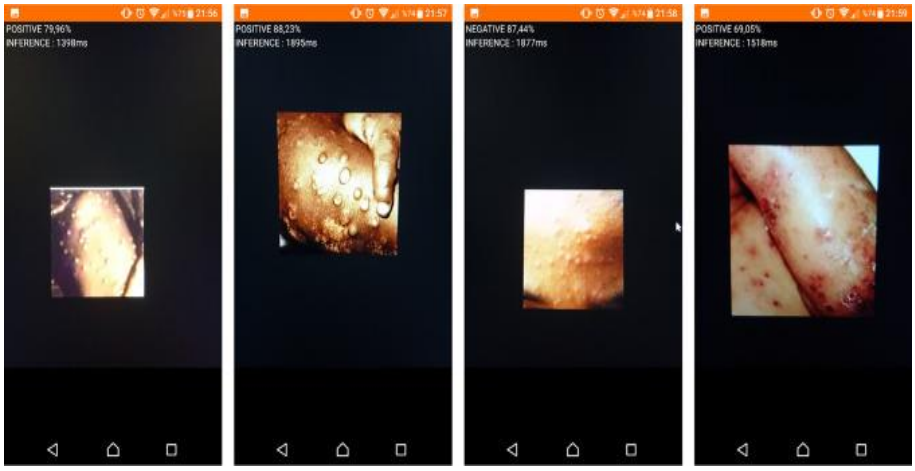

Figure 5. Sample screenshots from the mobile application. The first and second screenshots are samples of true positives, the third one is a true negative, and the last one is a false positive.

Table 6. Device information and performance.

Device Model	Android Version	CPU	RAM	Inference Time
Device 1	7.1.1	Octa-core Max 2.0GHz	3GB	197 ms
Device 2	10	Octa-core Max 2.2GHz	4GB	91 ms
Device 3	11	Octa-core Max 2.0GHz	4GB	138 ms

Conclusion

This study aimed to leverage deep learning-based methods to enhance the accuracy of monkeypox detection, presenting a novel software program that allows individuals to conduct screening for monkeypox using their mobile devices from the comfort of their homes. This innovative approach facilitates rapid response from affected individuals at various stages of infection, thereby aiding in delaying the onset of human monkeypox. The utilization of mobile devices for visual detection of monkeypox represents a pioneering endeavor in the field. The researchers systematically evaluated various deep learning-based methods, ultimately identifying a novel strategy based on the MobileNetV2 model that exhibited superior performance with an impressive accuracy rating of 99%. This newly proposed strategy surpassed the efficacy of models utilized in previous experiments, highlighting its potential for widespread application. Leveraging the resources provided by the Android platform, the authors developed an Android application for seamless implementation. However, it is noteworthy that multi-platform frameworks such as React Native, Flutter, or KMM, or even Progressive Web Applications (PWAs), could broaden the system's accessibility across diverse platforms. To further validate the model's effectiveness, future research endeavors should consider incorporating larger image sizes, which could enhance the system's robustness and accuracy. The study's findings hold significant promise for advancing the early identification, classification, and treatment of monkeypox. With exceptional accuracy demonstrated in both training and test sets, the researchers' model represents a cutting-edge machine learning approach for rapid monkeypox detection. This model has the potential to serve as a valuable tool for swift and precise diagnosis in clinical settings. Moreover, the continued accumulation of comprehensive and consistent data pertaining to the monkeypox virus can contribute to further enhancing the efficacy of the proposed system. Additionally, the developed technique holds promise for categorizing various other skin problems, thereby expanding its utility beyond monkeypox detection. Overall, this research marks a significant milestone in the realm of

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deep learning-based medical diagnostics and underscores the potential of technology-driven solutions in addressing public health challenges.

Conflict of interest

None

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